Enhancing Airline Recommendation Systems with Bayesian Networks: A Probabilistic Approach to Customer Feedback Analysis

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***Abstract*—This project deals with the development of an automated airline recommendation system, incorporating Bayesian Networks to analyze customers' feedback for a certain airline and to predict the likelihood of that airline being recommended. Customer feedback is the backbone of this model, which is captured through ratings on overall rating, value-for-money rating, cabin staff rating, seat comfort rating, food and beverages rating, and in-flight entertainment rating. This involves exploratory data analysis and correlation analysis to identify some key attributes the model will focus on for impactful variables. The Bayesian Network is a probabilistic graphical model that expresses these relationships and thus is accurate in prediction, yielding insight into customer satisfaction. Maximum Likelihood Estimation was used to train this model and learn conditional probability distributions of these relationships. Predictions are generated by performing inference, while performance is evaluated using accuracy. The model demonstrated strong predictive power as well as interpretability with which the airline operator explained the key drivers of recommended actions. This has ample potential for the airline's industry in enabling them target service improvements and customer satisfaction strategies. This algorithm can also be extended among other sectors such as hotels and retail, where customer experiences are very crucial.**

***Index Terms*—Bayesian Networks, Airline Recommendation, Probabilistic Modeling, Flask Web Application, Machine Learning.**

I. Introduction

Customer satisfaction is the prime motive behind the airline industry—a highly competitive business where companies aim to sustain growth and repeat business. Customer reviews and ratings provide valuable insights into airline services on various aspects of the carrier, such as ticket pricing, inflight amenities, comfort of seats, and service in general. Such feedback goes a long way in influencing prospective passengers and in shaping an airline's standing in the market. Analysis of such data often becomes challenging due to the presence of complexities in the data and the interdependencies among features. For example, ticket price drives perceptions of value for money, which in turn drives overall customer satisfaction. The complexities are best addressed by a strong probabilistic framework that can model feature dependencies effectively and predict customer recommendations.

Bayesian Networks (BNs) have been used here because they have the ability for graphical representation of complex dependencies, making them interpretable and accurate for probabilistic reasoning. Unlike other probabilistic models, such as Markov Chains or Naïve Bayes classifiers, Bayesian Networks can model multivariate dependencies between features; thus, they are suitable in datasets with interlinked variables such as customer ratings. For example, the rating of seat comfort, food and beverage, and inflight entertainment are not independent features; instead, they are related to each other in their contribution to the overall experience and customer recommendation. BNs capture the elaborate relationships among features, which in turn provide more fine-grained predictions.

Moreover, Bayesian Networks were also chosen because they can naturally incorporate prior knowledge with observed data, hence being robust for recommendation systems. Given its flexibility in feature dependencies handling, the model could effectively understand uncertainties inherent in the Customer Feedback data. Also, compared to other models in feature dependencies handling such as Naïve Bayes, Bayesian Networks assure superior explainability since overfitting is kept low in high-dimensional sets by this model. This combined reasoning makes Bayesian Networks suit best for the probabilistic modeling of this dataset relationship.

The presented research enriches the body of literature in the direction of Bayesian Networks employed in the airline industry, where probabilistic modeling has only slightly been explored. Thus, the model developed herein seeks to analyze interdependencies among the extracted key features based on the opinions of customers to yield correct predictions regarding the appropriateness of a recommendation of airlines. These results demonstrate a validity check that this approach might allow decision-makers with a potential tool for decision-making model functionality expansion at airline industries together with actionable insights for improvements regarding their customers.

II. Literature Survey

The use of Bayesian networks in predictive models related to aviation has been extensively studied. Zhang and Mahadevan [1] developed a robust framework for flight trajectory prediction using Bayesian neural networks, which helped address significant safety challenges in air transportation. By combining deep feedforward and LSTM neural networks, their method was able to capture trajectory deviations and long-term flight states, while also quantifying uncertainty in the model. Similarly, Gómez-Comendador et al. [2] applied Bayesian networks to model air traffic complexity, underscoring their ability to manage trajectory uncertainties and balance capacity in SESAR's demand-driven air traffic control systems. These studies illustrate how Bayesian networks provide scalability and precision in safety-critical aviation applications.

Bayesian networks have also been explored for analyzing customer reviews and recommendations. Siering et al. [3] examined the predictive power of consumer-generated online reviews, employing sentiment analysis and machine learning models to predict airline recommendations. Their research identified key service aspects that influence customer decisions and offered valuable insights for improving customer satisfaction in competitive markets. Additionally, Zhang and Mahadevan [4] used Bayesian networks to analyze aviation accident investigation reports, modeling causal relationships to enhance risk assessments and decision-making. These studies emphasize the value of Bayesian networks in recommendation systems and their ability to handle interdependencies among various features.

Bayesian networks have also found applications in aviation maintenance and diagnostics. Ferreiro et al. [5] introduced a Bayesian network-based prognostic model to estimate the remaining useful life of aircraft components, demonstrating the utility of Bayesian networks in predictive maintenance. Sahin et al. [6] combined Bayesian networks with distributed particle swarm optimization to develop a fault diagnosis system for airplane engines, highlighting their scalability and efficiency. Furthermore, Correa et al. [7] compared Bayesian networks with artificial neural networks for quality detection in machining processes, showcasing their interpretability and diagnostic capabilities. These studies validate the versatility of Bayesian networks across various domains, highlighting their effectiveness in probabilistic reasoning and decision support.

The adaptability of Bayesian networks extends beyond aviation into fields like operational risk management and supply chain optimization. Neil et al. [8] used Bayesian networks to model operational losses in financial risk management, particularly in cases of sparse or uncertain data. Their approach combined expert judgment with historical loss data, enabling predictions of both expected and unexpected losses while performing sensitivity analyses to identify key influencing factors. Similarly, Yorukoglu and Kayakutlu [9] applied Bayesian networks to optimize aviation supply chains, focusing on delays and complaints from disabled passengers. Their model identified critical factors such as baggage handling and check-in efficiency, offering actionable insights to improve service quality. Morales et al. [10] demonstrated the use of Bayesian network classifiers in predicting dementia progression in Parkinson's disease, showing how Bayesian networks could incorporate neuroanatomical biomarkers for accurate diagnostic predictions. Collectively, these studies highlight the broad applicability of Bayesian networks in managing uncertainty and performing probabilistic reasoning across complex fields.

III. Methodology

A. Data Collection

The dataset used in this project consists of customer reviews and ratings from various airlines, providing insights into passengers' experiences across different aspects of airline services. Key features include overall rating, value-for-money rating, cabin staff rating, seat comfort rating, food and beverage rating, and in-flight entertainment rating. Additional information such as airline name, route, traveler type, cabin class, and textual feedback provide valuable context for the numerical ratings. Missing values in the dataset were handled by imputing the mode for categorical columns and the mean for numerical columns. Categorical features like 'traveler type' and 'cabin class' were encoded using one-hot encoding to make them suitable for machine learning models. For feature selection, only attributes strongly correlated with the target variable, "recommended", were retained to enhance the model's accuracy and interpretability. The dataset was then split into training and testing subsets, and the target variable was separated from the predictors. This extensive preprocessing was done to prepare the dataset for building a Bayesian Network model to analyze the probabilistic relationships between features and predict customer recommendations.

B. Data Preprocessing

Preprocessing the data is a critical step to ensure the dataset is of high quality and suitable for developing a robust machine learning model. Several preprocessing techniques were applied to the dataset, including handling missing values, encoding categorical variables, and selecting relevant features for modeling.

To start, missing values were addressed to maintain data integrity. For numerical columns, missing values were filled using the mean of the respective column, while categorical columns were imputed with their mode. This approach preserved the dataset's distribution and minimized potential bias.

Categorical variables such as type_traveller ,cabin_flown and route were transformed using one-hot encoding, which converted them into binary columns. This made them suitable for use in the Bayesian Network model. For the numerical features, standardization was applied to normalize their scales, which helped improve the model's performance and interpretability.

Feature selection was also performed to reduce dimensionality and focus on the most impactful attributes. Features that were highly correlated with the target variable, "recommended", were identified using a correlation matrix, and those surpassing a certain threshold were retained. This step helped eliminate redundant or irrelevant features, simplifying the model and enhancing its accuracy.

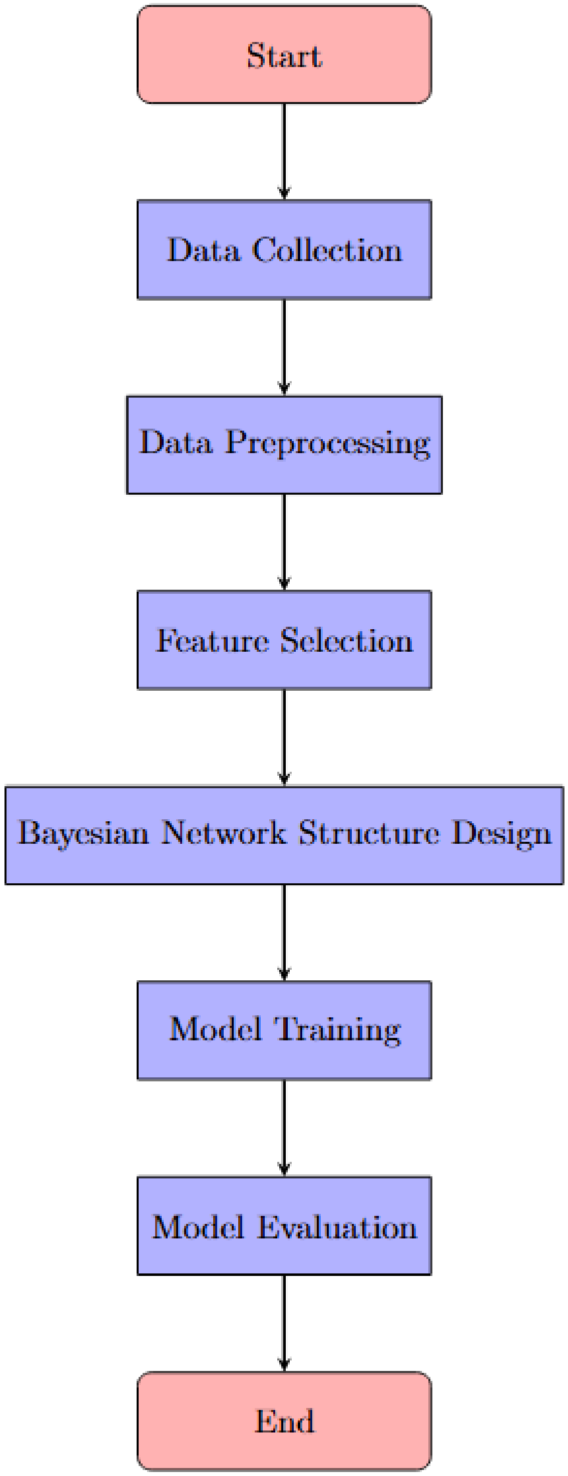

Fig. 1: Flow Chart Diagram

C. Feature Selection

Feature selection is a crucial step in building a model that is both efficient and interpretable. By identifying the most important features in the dataset, we reduce dimensionality, improve computational efficiency, and enhance the model's predictive accuracy. In this project, feature selection was performed using a correlation matrix to examine the relationships between variables and their relevance to the target variable, "recommended." The correlation matrix helped us understand the interdependencies between features by quantifying their linear relationships. Features with the highest absolute correlation to the target variable were prioritized for inclusion. This approach ensured that the chosen features had a meaningful impact on predicting customer recommendations, while irrelevant or redundant features were excluded to reduce noise in the model.

From this analysis, the most influential features in predicting airline recommendations were identified as: Overall Rating, Value-for-Money Rating, Cabin Staff Rating, Seat Comfort Rating, Food and Beverages Rating, and Inflight Entertainment Rating. These features capture various dimensions of the customer experience, from inflight service quality to the perceived value of ticket pricing. By focusing on these key features, the model strikes a balance between complexity and interpretability, capturing the essential probabilistic relationships needed for accurate predictions. The selected features provide a comprehensive view of customer satisfaction, making the Bayesian Network model both effective and practical for addressing the airline recommendation problem.

The Bayesian Network is a probabilistic graphical model designed to represent the dependencies between six key features (Overall Rating, Value-for-Money Rating, Cabin Staff Rating, Seat Comfort Rating, Food and Beverages Rating, Inflight Entertainment Rating) and the target variable, "recommended." This structure was manually defined using domain knowledge to ensure logical dependencies that reflect real-world relationships. The directed edges in the network represent the influence of each feature on the target variable, with each feature acting as a parent node to "recommended." During training, the relationships between variables were quantified using Maximum Likelihood Estimation (MLE), generating Conditional Probability Distributions (CPDs) that estimate the likelihood of a customer recommending the airline based on the ratings. This approach not only ensures that the predictions are interpretable but also provides valuable insights into the key factors influencing customer satisfaction and recommendations.

D. Implementation

The focus of the implementation of this project was on designing Training and evaluation of a Bayesian Network model to predict customer recommendations based on feedback ratings. This sec- tion details the steps involved, from model training to evaluation. Model Training: The Bayesian Network was implemented us- ing the pgmpy library - a Python library designed for probabilistic graphical models. To construct the network, one manually predefined A structure was, therefore, created based on domain knowledge and represented Logical dependencies among six key features: Overall Rating, Value-for-Money Rating, Cabin Staff Rating, Seat Comfort Rating, Food and Beverages Rating, and Inflight Entertainment Rating) and the target variable (recommended). This structure ensured that the model captured meaningful relationships between the variables, the interpretable and realistic network. For training, Maximum Likelihood Estimation (MLE) was used to estimate the Conditional Probability Distributions (CPDs) of each node in the network. MLE is an established method for parameter estimation in Bayesian Networks, using ob- served data to compute probabilities that maximize the likelihood of the given data under defined model. In this process, The learning of joint probabilities of the combination of features was performed. which will allow the network to model the probabilistic dependencies. The correlation between variables effectively. The dataset was preprocessed to ensure compatibility with pgmpy: also encode categorical variables and standardizing the structure for training.

Model Evaluation: To check the generalizability and reliability of the trained Bayesian Network, testing was done using a different test dataset. For testing, the performance of the model in terms of accuracy was considered, defined as the ratio of correct recommendations, both positive and negative, to the total number of predictions. This model attained 92% accuracy, hence showing high predictive performance and proving its capability of capturing probabilistic relationships among customer feedback features.

A confusion matrix has been generated in understanding the class outcome for true positives: correct recommendations predicted, true negatives: correct no-recommendation predictions, false positives, recommendations mis-predicted, and finally, false negatives or missed recommendations. This can then establish strengths in the understanding of how the model was performed to forecast correct recommendations, with great pragmatic relevance to customer feedback analysis. In the end, dependency on accuracy as a main evaluation metric was enough for the objectives of this project: to clearly point to the overall effectiveness of the model.

The suitability for application was brought out very well by the Bayesian Networks, especially with regard to the capture of interdependencies among features, and with the transparency in decisions enabled. The structured approach makes sure the model handles the uncertainties while providing interpretable results. This could be a valuable tool for understanding customer behavior in the airline industry.

IV. Results

A. Model Accuracy

The Bayesian Network achieved a high accuracy of 90.99% on the test dataset, demonstrating its ability to effectively predict customer recommendations based on feedback. The accuracy reflects the network's ability to capture probabilistic relationships between features and the target variable, leveraging the structured dependencies inherent in the data.

B. Confusion Matrix

The confusion matrix, as shown in Figure 2, provides a detailed breakdown of the model's performance. It highlights the following metrics:

- True Positives (TP): The model correctly identified 3813 instances where the airline was recommended.
- True Negatives (TN): It correctly classified 3721 instances where the airline was not recommended.
- False Positives (FP): 145 instances were incorrectly predicted as recommendations.
- False Negatives (FN): The model missed 601 instances where the airline was recommended but predicted otherwise.

The high values of TP and TN indicate the robustness of the Bayesian Network in identifying both positive and negative cases accurately. The relatively low FP and FN rates further validate the model's reliability.

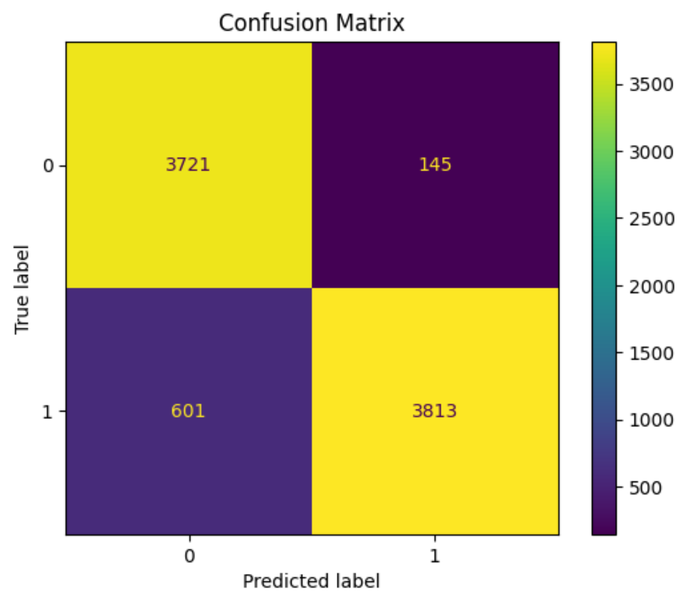

Fig. 2: Confusion Matrix of the Bayesian Network Model

C. Discussions

The results obtained are a direct outcome of the systematic preprocessing steps undertaken during the data preparation phase. Each step played a critical role in enhancing the model's predictive performance:

- Handling Missing Values: Missing values in the dataset were imputed using median values to retain the integrity of the data while avoiding the loss of valuable records. This step ensured a complete dataset, contributing to a well-rounded training process.
- Encoding Categorical Variables: Features such as cabin class and type of traveler were encoded into numerical representations. This allowed the Bayesian Network to effectively incorporate these variables into its probabilistic model, preserving the interpretability of categorical relationships.
- Feature Selection using Correlation Matrix: Features with the strongest correlation to the target variable 'recommended' were retained. This step removed irrelevant or

weakly correlated features, reducing noise and improving the model's focus on impactful predictors.

- Normalization of Ratings: Customer ratings for services like seat comfort and inflight entertainment were normalized to ensure that all features contributed equally to the model. This avoided dominance by features with larger numerical ranges.
- Binning of Numerical Features: Continuous variables, such as *overall rating*, were binned into discrete categories (e.g., low, medium, high). This enhanced the Bayesian Network's interpretability by aligning with its probabilistic framework, which works more efficiently with discrete data.
- Balancing the Dataset: The dataset was examined for class imbalance, and any disproportionate representation of the target variable was mitigated to ensure fairness in training and testing phases. This step was crucial for reducing bias in the predictions.

V. Conclusion

The Bayesian Network-based recommender system for airlines really demonstrates how effective probabilistic reasoning can be in decision-support applications. Bayesian Networks are especially useful in situations where interpretation of the relationships among variables-for example-is an integral part of the task at hand; they model the dependencies in an interpretable manner. The system makes reliable predictions of whether an airline would be recommended or not, based on the probabilistic relations between the customer ratings and their respective service quality. This functionality enables not only better decision-making but also deep insight into the determinants of customer satisfaction and is, therefore, considered an effective tool for data-driven applications in the airline industry.

Further enhancements can be made in the future for better functionality and scalability of the system. More features like ticket pricing, flight duration, and customer demographics may complete the model. Other probabilistic reasoning methods or hybrid approaches might further strengthen the accuracy and performance in predictions. Hosting the models on cloud platforms like AWS and Azure would enable real-time scaling of predictions for broader end-user access. Adding multilanguage support and building a feedback loop to continuously update this model with user inputs may be some other ways the system can be enhanced from a usability and effectiveness-for-diverse-audience perspective.

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